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ROULETTE ANT WHEEL SELECTION (RAWS) FOR GENETIC ALGORITHM – FUZZY SHORTEST PATH PROBLEM

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ABSTRACT

Many applications such as robotics, communication, transportation, scheduling, routing and mapping where, the shortest path problems are applied importantly. Shortest path problem is nothing but determines the continuous shortest path from source vertex to the destination vertex in the graph G=$\{V, E\}$. While considering a network, the arc length may represent distance, time, bandwidth or cost. But, in real life applications, there is certain uncertainty in the representation of real values as the arc length which in turn gives raise to fuzzy shortest path. In fuzzy shortest path problem, the edges are represented by fuzzy numbers and here we use generalized trapezoidal fuzzy numbers. The distance between the fuzzy edges is known to be fuzzy distance which comprises of centroid points, left spread and right spread. Genetic Algorithm (GA) is the most powerful among the optimization methods which involves 'natural selection' and the survival of the best individual to next generation. We are dealing with the individual genetic operators and here we concentrate on the selection operation because of its importance in convergence and selection pressure of Genetic Algorithm (GA). We propose Roulette Ant Wheel Selection (RAWS) which hybrids the characteristics of ants and the roulette wheel selection algorithm. Our objective is to analyse how the selection operation contributes in upgrading GA.

KEYWORDS: Genetic Algorithm, Ant Colony, Generalized Trapezoidal Fuzzy Number, Roulette Wheel Selection, Ranking Function, Shortest Path Problem

Mathematics Subject Classification: 03B52, 03E72

1. INTRODUCTION

The shortest path problem has more important to determine the shortest distance between the source and destination. Many applications such as robotics, communication, transportation, scheduling, routing and mapping where, the shortest path problems are applied importantly. While considering a network, the arc length may represent distance, time, bandwidth or cost. Therefore, in real life applications, it is advisable to be a fuzzy set. Fuzzy set theory, proposed by Zadeh [14], is frequently used to accord with uncertainties in a problem.

We consider a directed network G = {V, E} where V represents the finite collection of vertices (vertices) and E represents the finite collection of directed edges. The assumption is made possibly as single directed edge is allowed between vertices. A source vertex and a destination vertex are specified and each edge length is represented by a generalized trapezoidal fuzzy number, and the length of a path is defined to be the fuzzy sum of edge lengths along the path and also distance measure is used. We are formulated so as in finding an optimized path from the source vertex to destination vertex while optimizing the fuzzy length of the path using the properties of generalized fuzzy numbers. Blue et

al. [4] give taxonomy of network fuzziness that distinguishes five basic types combining fuzzy or crisp vertex sets with fuzzy or crisp edge sets and fuzzy weights and fuzzy connectivity.

Fuzzy distance is the distance between two fuzzy numbers and generalized Hamming and Euclidean distances have reviewed [8] and proposed new distance measure based on the similarities of fuzzy numbers. Abbasbandy [1] reviewed various distance measure and characterize each methods along various dimensions and proves it with numerical example. Ebadi [7] proposed the new distance measure of fuzzy numbers based on the centroid points

Genetic Algorithm (GA) is the most powerful among the optimization methods which involves ‘natural selection’ and the survival of the best individual to the next generation. The major operations of the genetic algorithm will be described in forthcoming sections. ZainudinZukhri [15] proposed hybrid ant based genetic algorithm and compares the results obtained from genetic and proposed algorithm where the proposed algorithm gives more efficient in the convergence than genetic and ant colony optimization algorithms. Cauvery [5] proposed mobile agents in genetic algorithm where ants are used as mobile agents. The population initialization is done with the ants and rest of the algorithm proceeds with genetic algorithm and results in finding the shortest path more effectively and also in load balancing. Shang Gao[13] proposes a novel ant colony genetic algorithm in which genetic and ant colony algorithm is mixed up and different mutation operation is carried out to select the best outcome. The results provide the way of combining both algorithms.

In genetic algorithm, selection of individual for the next generation is more important in the convergence of the algorithm. Selection operation is also capable of controlling the selection pressure where percentage of selection pressure is defined to be ratio of minimal possible number of generation from all the parent selection for which the best individual dominates in the population to the total number of generation in which the best solution dominates in the generation. Hence we concentrate on the selection operation to select the best individual for the next generation and also with the constraints of removal of non continuous paths without affecting the natural selection concept of genetic algorithm.

Khalid Jebari [10] review the various selection operation of genetic algorithm that mainly used often and proposed the mean population diversity between the selection operations in which selection among various methods is compared and best individual is selected for next generation. Razali [11] compares the roulette wheel selection of rank based and proportional based. The objective of the comparison is to analyze the solution quality and the number of generations taken by the best solution to dominate. It concludes that the rank based roulette wheel selection is best among the reviewed selection though tournament selection has high convergence and less execution time for small size problems.

This paper is organized as follows. In section 2, some basic definitions are reviewed and discussed. Section 3 briefs the network terminology. Section 4 explains the proposed approach of Genetic Algorithm (GA). Section 5 reviews the Roulette Wheel Selection (RWS) along with its drawbacks. Section 6 describes the proposed Roulette Ant Wheel Selection (RAWS) used in the selection operation of Genetic Algorithm (GA) along with the algorithm. In section 7, numerical example along with the example calculation is given. Section 8 deals with the results and discussion. And paper ends with the conclusion and future enhancement in section 9.

2. BASIC DEFINITIONS

The basic definitions of some of the required concepts are reviewed [9] in this section.

2.1 Fuzzy Set

Let X be an universal set of real numbers R, then a fuzzy set is defined as

A= {[x, $\mu_{\tilde{A}}$(x)], x ϵ X}

This is characterized by a membership function: X → [0 1], Where, $\mu_A(x)$ denotes the degree of membership of the element x to the set A.

2.2 Characteristics of Generalized Fuzzy Number

A fuzzy set $\tilde{A}$ which is defined on the universal of discourse *R*, is known to be generalized fuzzy number if its membership function has the following characteristics

- $\mu_A : R \to [0,1]\ iscontinuous.$
- $\mu_A(x) = 0\ forallx \in (-\infty, a] \cup [d, \infty).$
- $\mu_A(x) isstrictlyincreasingon[a,b]andstrictlydecreasingon[c,d].$
- $\mu_A(x) = w, forallx \in [b,c], where\ 0 < w \le 1.$

2.3 Membership Function of Generalized Trapezoidal Fuzzy Number

A generalized trapezoidal fuzzy number $\tilde{A}$ = (a,b,c,d;w) is known to be a generalized trapezoidal fuzzy number, if its membership function is given by

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{w(x-a)}{(b-a)} & a \le x \le b \\ 1 & b \le x \le c \\ \frac{w(x-d)}{(c-d)} & c \le x \le d \end{cases}$$

Let $\tilde{A} = (a,b,c,d;w)$ be a generalized trapezoidal fuzzy number then

a) $R(\tilde{A}) = \frac{w(a+b+c+d)}{4}$, b) M($\tilde{A}) = \frac{w(b+c)}{2}$, c) divergence $D(\tilde{A}) = w(d-a)$, d) Left spread $LS(\tilde{A}) = w(b-a)$, e) Right spread $RS(\tilde{A}) = w(d-c)$

2.4 Fitness Function for Ranking

Let $\tilde{A}$= $(a_1,b_1,c_1,d_1;w_1)$ and $\tilde{B}$= $(a_2,b_2,c_2,d_2;w_2)$ be two triangular fuzzy numbers then the addition is defined by $\tilde{A} \oplus \tilde{\boldsymbol{B}}$ = $(a_1+a_2, b_1+b_2, c_1+c_2, d_1+d_2; w_1+w_2)$

2.5 Ranking of Generalized Trapezoidal Fuzzy Numbers

Let A = $(a_1, b_1, c_1, d_1; w_1)$ and B = $(a_2, b_2, c_2, d_2; w_2)$ be two generalized trapezoidal fuzzy numbers then use the following steps [3] to compare A and B

Step 1: Find R (A) and R (B)

Case (i) If R (A) > R (B) then A > B

Case (ii) If R (A) < R (B) then A < B

Case (iii) If R (A) = R (B) then go to step 2.

Step 2: Find mode M (A) and mode M(B)

Case (i) If mode M (A) > mode M (B) then A > B

Case (ii) If mode M (A) < mode M (B) then A < B

Case (iii) If mode M (A) = mode M (B) then go to step 3.

Step 3: Find divergence D (A) and divergence D (B)

Case (i) If divergence D (A) > divergence D (B) then A > B

Case (ii) If divergence D (A) < divergence D (B) then A < B

Case (iii) If divergence D (A) = divergence D (B) then go to step 4.

Step 4: Find Left spread LS (A) and Left spread LS (B)

Case (i) If Left spread LS (A) > Left spread LS (B)

i.e, $w_1b_1 > w_2 b_2$ then A > B

Case (ii) If Left spread LS (A) < Left spread LS (B)

i.e, $w_1b_1 < w_2 b_2$ then A < B

Case (iii) If Left spread LS (A) = Left spread LS (B)

i.e, $w_1b_1 = w_2 b_2$ then go to step 5

Step 5 Find w_1 and w_2

Case (i) If $w_1 > w_2$ then A > B

Case (ii) If $w_1 < w_2$ then A < B

Case (iii) If $w_1 = w_2$ then A ~ B

2.6 Fitness Function for RAWS Selection

Jahantigh [8] described the relation between generalized trapezoidal fuzzy number (a, b, c, d; w) and trapezoidal fuzzy number (a, b, c, d) that the trapezoidal fuzzy number has value of w=1 whereas generalized trapezoidal fuzzy number has the range $0 \leq w \leq 1$ and also described the relation between generalized triangular(a, p, q; w) and trapezoidal (a, b, p, q; w) fuzzy numbers in which trapezoidal is equivalent to trapezoidal having a=b.

The distance measure between the generalized trapezoidal fuzzy numbers $\tilde{A}(a_1,b_1,c_1,d_1;w_1)$ and $\tilde{B}$ $(a_2,b_2,c_2,d_2;w_2)$ using centroid points (α, β) of $\tilde{A}$ is given by [7]

$$f_d(\tilde{A},\tilde{B}) = \max\{|\alpha_{\tilde{A}} - \alpha_{\tilde{B}}|, |\beta_{\tilde{A}} - \beta_{\tilde{B}}|, |R(\tilde{A}) - R(\tilde{B})|, |LS(\tilde{A}) - LS(\tilde{B})|, |RS(\tilde{A}) - RS(\tilde{B})|\}$$

where $\alpha = \frac{1}{3}\left[a_1 + a_2 + a_3 + a_4 - \frac{a_4 a_3 - a_1 a_2}{(a_4+a_3)-(a_1+a_2)}\right]$ and $\beta = \frac{1}{3}\left[\frac{a_3 - a_2}{(a_4+a_3)-(a_1+a_2)}\right]$

3. NETWORK TERMINOLOGY

Consider the directed network G (V, E) consisting of a finite set of vertices V={1,2……n} and a set of m directed edges E $\subseteq V \times V$. Each edge is denoted by an ordered pair (i,j) where i, j $\in$ v and i$\neq$ j. In this network, we specify two vertices namely source vertex and the destination vertex. $\widetilde{d_{ij}}$ denotes the generalized trapezoidal fuzzy number associated with the edge (i,j). The fuzzy distance along the path P is given in section 2.6.

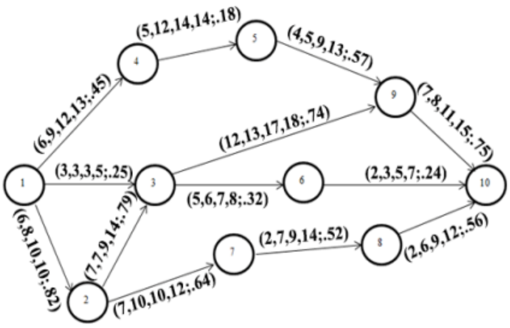

Figure 1

4. GENETIC ALGORITHM

Genetic Algorithm (GA) is a type of Evolutionary Algorithm (EA) which is based on the natural selection phenomenon. GA usually has an analogy to the randomness in solving a problem. It is comprised of generations where children are produced by the mating of the parents with genetic operators. Selection and reproduction to produce efficient generation is based on the random procedures, known to be natural selection.

4.1 Representation of an Individual (Chromosome)

Each chromosome is represented in binary representation and it is also important which represents the solution in the generations. The representation defines the path traversed and indirectly refers the fuzzy fitness of the chromosome. The number of bits used in representing chromosome is equal to the number of vertices in the network graph G= {V, E}. The vertex visited is represented by 1 and 0 represents that the vertex is not visited.

Here, we take 10 vertices network and the representation 1101100001 represents that the path traversed may be 1-2-4-5-10, 1-2-5-4-10, 1-4-2-5-10, 1-4-5-2-10, 1-5-4-2-10 and 1-5-2-4-10 depending on the existence.

4.2 Population Initialization

The initial population is generated randomly in usual GA and each chromosome represents the collection of edges which are represented by generalized trapezoidal fuzzy numbers explained in previous sections. The default population size 20 is used.

4.3 Selection Operation

Selection operation is used in initialization process and parent selection for crossover operation. Various selection operations involve Roulette wheel selection, Random selection, Rank selection, Tournament selection and Boltzmann selection [12].

Here we proposed Roulette Ant Wheel Selection (RAWS) which selection the optimal solution through quantitative randomness in the population. Ants use its pheromone in which best solution has more pheromone and worst has less pheromone. Thus the best solution with the least number of traversal or better solutions with more number of traversal is selected.

4.4 Crossover Operation

Crossover operator mates two parent chromosomes and produces children which comprise the essence of two parent chromosome mated. Crossover operation is mainly categorised into two single point and multi point crossover

The single point crossover has single crossover site whereas multi point crossover has more than single crossover site. There are also some advanced multipoint crossover methods [12] and here we use two point crossover technique with crossover rate of 0.3.

Consider an example with two parent chromosome A (1011001111) and B (1001101001). Two point crossover has to be carried out with a rate of 0.3. The points have to be generated randomly.3.

Parent 1	1	0	1	1	0	0	1	1	1	1
Parent 2	1	0	0	1	1	0	1	0	0	1

Child 1	1	0	1	1	0	0	1	0	0	1
Child 2	1	0	0	1	1	0	1	1	1	1

4.5 Mutation Operation

The conventional mutation operator performs the minute changes of the reproduced child randomly under a certain rate which undo the degradation of the population due to crossover operation.

There were many mutation operations for binary and real integers. Here we choose binary mutation that may be bit flipping, insertion, interchanging, reciprocal exchange, inversion and others [2].

Here bit flipping is used as mutation operation that carried out using bit complement. Bit complement is nothing but reversing the bits as 1 for 0 and 0 for 1 respectively. The mutation operation is carried out at the rate of 0.1.

After the mutation, the obtained chromosome is validated whether the path is continuous and exists in the network. The existed chromosome has sent for the fitness calculation and when the fitness is better than its parents, it will be replaced with parents and used for further generations. The non-continuous chromosomes are discarded.

1	0	1	0	1	0	0	1	0	1

Before Mutation Operation

1	0	1	0	0	0	0	1	0	1

After Mutation Operation

4.6 Termination Condition

Termination condition produces the optimal solution through the convergence. Mostly termination condition will

be the maximum number of generations. Other conditions are the idealness of the chromosomes in the generation. In order to test the algorithm, maximum number of generations can be used as termination condition which clearly represents the convergence of the algorithm.

Here, idealness of the chromosomes is considered as termination condition because of the usage trapezoidal fuzzy numbers and uncertainty in real numbers. When no change in the optimal fitness (minimal) and the idealness of the chromosomes in generations for at least 5 generations, then the algorithm reaches the termination condition.

5. ROULETTE WHEEL SELECTION (RWS)

Roulette wheel selection method also known as fitness proportionate selection has described in [6] that it works as per the roulette wheel game. The fitness of the individual in the generation is proportional to the likelihood of the individual chosen in this algorithm. The fitness of the individual is also inversely proportional to the size of each individual 'slice' of the roulette wheel. After the determination of the 'slices', a random number is generated which is used to select the parent. The generated random number, where it matches with the range of numbers individual contains will be selected as the parent in this iteration. The method can be continued till the need of the parents selected in which each method selects a parent.

The background of roulette wheel selection uses the fitness functions assign to every individual solution in the population. The probability function of the selection of individual where $f_i$represents the fitness of individual i, N represents the size of the population and the probability function p_i is given by

$$p_i = \frac{f_i}{\sum_{j=1}^{N} f_i}.$$

According to the drawback of the algorithm stated in [10], the probability of the risk of premature convergence of genetic algorithm to a local optimum is because of the dominance of the worst individual on the best solution which in turn the worst solution is selected.

6. ROULETTE ANT WHEEL SELECTION (RAWS)

Roulette Ant Wheel Selection works on the Roulette wheel principle which contributes to the randomness along with the fitness measure in the selection of parents. This algorithm is not only focused on randomness as proposed in Roulette Wheel Selection (RWS) [6, 10] but also focused on the criteria of best selection in the population. RAWS consists of Roulette wheel, Inner Cyclic Ant (ICA) and Outer Cyclic Ant (OCA).

6.1 Roulette Wheel

Roulette wheel has the chromosomes sequentially arranged as the numbers in the Roulette game as shown in the Figure 2 Inner circle of the wheel has to be filled with Inner Cyclic Ants (ICA) and outer circle of the wheel has to be filled with Outer Cyclic Ants (OCA) in which both traverses the chromosomes.

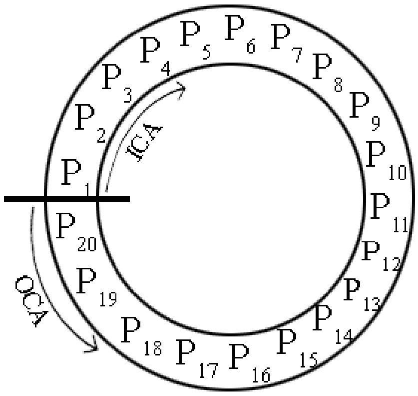

Figure 2: Roulette Ant Wheel

In the proposed algorithm, Roulette wheel is not rotated but the ants (ICA and OCA) used traversed the wheel through clockwise and anti-clockwise directions respectively. The chromosome of the population in the wheel is also represented by its fitness value calculated by the fitness function described in previous section.

6.2 Inner Cyclic Ants (ICA)

Inner Cyclic Ants (ICA) present in the inner circle of the Roulette wheel traverses the chromosomes in clockwise direction. The ICAs are positioned in random chromosome and the next chromosome ICA has to be traversed is also made as random. Whenever the chromosome is traversed, the pheromone is shed.

Since the shortest path has the less fitness and proposed pheromone is inversely proportional to the fitness, a chromosome having small fitness value reaches the maximum pheromone in least number of traversal than the chromosomes having the larger fitness. Hence chromosome of small fitness with least number of traversal or chromosome of large fitness with most number of traversal has high pheromone.

When chromosome with certain value of pheromone is traversed by any of the ICAs, the traversal is temporarily stopped and checks for the OCAs whether they met the same condition. The pair of chromosome with high pheromone is selected shown in Figure 2, if and only if both ICAs and OCAs met the same condition.

6.3 Outer Cyclic Ants (OCA)

Outer Cyclic Ants (OCA) present in the outer circle of the Roulette wheel traverses the chromosomes in anti-clockwise direction. The OCAs are positioned in random chromosome and the next chromosome OCA has to be traversed is also made as random. Whenever the chromosome is traversed, the pheromone is shed.

When chromosome with certain value of pheromone is traversed by any of the OCAs, the traversal is temporarily stopped and checks for the ICAs whether they met the same condition. The pair of chromosome with high pheromone is selected, if and only if both ICAs and OCAs met the same condition.

6.4 General Characteristics of Ants

- The number of ants selected for both ICA and OCA are given by $^{n}/_{4}$, where n represents the size of the population.

- The positions of the ants placed in both inner and outer circles are made as random.
- The next chromosomes traversed by ants are also selected randomly with clock and ant-clock wise directions for ICA and OCA respectively.
- Anti-clockwise traversal can be achieved by OCA through $(n - rand)$ moves along clockwise direction, where $rand$ is the actual position that has to be moved in anti-clockwise direction.
- Whenever chromosome is traversed, pheromone is shed in that chromosome and the pheromone $P_{mone}()$ is given by (6.1)
- While any of the ants in ICA reaches the $P_{mone}(max)$ given in (6.2), ICA stops its traversal and checks whether OCA reaches the $P_{mone}(max)$ and vice versa.
- When both ICA and OCA attains $P_{mone}(max)$ state, the chromosome having high pheromone from both ICA and OCA is selected.
  - A selection should be done that chromosome selected by ICA and OCA is not same.
  - Fuzzy ranking given in section 2.5 is used when two or more chromosomes have same pheromone.
  - Any ant in both ICA and OCA with suitable criteria is always taken into account.

Roulette Wheel Ant Selection (RAWS) uses a random best selection criteria in selection the individuals as the parents of next generation. This algorithm should not spoil the principle of Genetic Algorithm (GA) 'Natural selection' but keep tracks on the selection of best individual. In shortest path algorithm, the least fitness becomes the best solution and the pheromone $P_{mone}()$ is formulated inversely to the fitness, i.e. inversely proportional to the fitness value. Hence chromosome of least fitness is shed by the ants with greater pheromone.

$$P_{mone}(P_i) = \begin{cases} \frac{1}{\sqrt{(2f(i)-low)^2+f(i)^2}}, & f(i) \neq 0 \\ 0; & otherwise \end{cases} \tag{6.1}$$

Where P_i represents ith chromosome in the population P and $f(i)$ represents the fitness value of the ith chromosome in the population P. Since the fitness value of non-continuous individuals cannot be determines, it is taken as zero and the pheromone of the same is taken as zero or null.

$$P_{mone}(max) = \frac{\sqrt{(high^2 - low^2)}}{\sqrt{(high^2+(high+low)^2)}}, high \neq low. \tag{6.2}$$

The stopping criteria of the selection $P_{mone}(max)$ can be calculated with the help of high and low fitness values in the population in which both should be greater than zero ($high, low > 0$).

Algorithm

Step 1: Initialize the population with size n and calculate the fitness values of each chromosome.

Step 2: Place $^{n}/_{4}$ ants randomly as ICA and OCA in inner and outer circle respectively.

Step 3: Calculate $P_{mone}(max)$ given in (6.2) with the help of high and low fitness values in the generation.

Step 4: Move the ants in ICA and OCA through clockwise and anti-clockwise direction randomly that chromosome which has to be visited next is selected in random manner.

Step 5: Whenever the chromosome is visited, the pheromone $P_{mone}()$ given in (6.1) is shed to the chromosome.

Step 6: Repeat steps 4 and 5 till $P_{mone}()$ of any of the ants from ICA and OCA reaches $P_{mone}(max)$ and also checks that the chromosome reaches $P_{mone}(max)$ indicated by ICA and OCA should not be same.

Step 7: The chromosome having highest $P_{mone}()$ from both ICA and OCA are selected and it should not be same chromosome.

Step 8: Fuzzy ranking given in section 2.5 is used in case one or more chromosomes have highest pheromone.

The possible conditions in which randomly generated population initialization where non-continuous paths have no fitness and pheromone obliviously ruins the natural selection process. It is clearly observed that the proposed selection is very suitable for individuals of continuous path and also in case for some continuous individuals. Hence it is necessary to concentrate on population initialization and has to be initialized with continuous individuals.

7. NUMERICAL EXAMPLE

Let us consider the network graph G= {V, E} which is described in section 3. Numerical example of proposed RAWS method involves population initialization, fitness calculation, ant's initialization, ant's traversal, pheromone calculation and ranking analysis.

The representation and initialization of individual is already explained in the section 4.1 and 4.2. The fitness can be calculated in two different ways in which one is based on distance measure $f_d()$ (section 2.6) for proposed method and other is addition of fuzzy numbers $f_a()$.

Table 1: Sample Calculation $f_d()$ of Path 1-3-6-10 (Continuous Path)

Path	Next Vertex	$f_d(\tilde{A},\tilde{B})$ **(Section 2.6)**
1	3	0
1-3	6	0+2.833=2.833
1-3-6	10	2.833+2.214=5.047

Table 2: Sample Calculation $f_d()$ and $f_a()$ of Path 1-4-5-6-10 (Non Continuous Path)

Path	Next Vertex	$f_d(\tilde{A},\tilde{B})$	$f_a(\tilde{A},\tilde{B})$ **(Section 2.4)**
1	4	0	(6,9,12,13;.45)
1-4	5	0+2.475=2.475	(11,21,26,27;.63)
1-4-5	6	(not exist)	(11,21,26,27;.63)
1-4-5-6	10	0	(13,24,31,34;.87)

Table 3: Samples of Individuals Along with the Fitness Measure of the Population

Chromosome	Path	$f_d(\tilde{A},\tilde{B})$	$f_c(\tilde{A},\tilde{B})$
p_4	1-3-6-10	5.047	(10,14,15,20;.81)
p_8	1-3-9-10	14.746	(22,27,31,38;1.74)
p_{12}	1-4-5-6-10	-	(13,24,31,34;.87)
p_{16}	1-4-5-9-10	9.599	(22,34,46,55;1.95)
p_{20}	1-3-6-8-10	-	(10,15,19,25;1.13)

The ants of ICA and OCA move randomly that it always sheds the pheromone (6.1) and this continues till the maximum pheromone (6.2) is obtained.

Let consider path P_{16} 1-4-5-9-10with the fitness value $f_d(\tilde{A},\tilde{B}) = 9.599$. The pheromone can be calculated with $low = 5.047\ and\ high = 14.746$ as

$$P_{mone}(P_4) = \frac{1}{\sqrt{(2f(i)-low)^2+f(i)^2}} = \frac{1}{\sqrt{200.25+92.14}} = \frac{1}{17.099} = 0.0585$$

$$P_{mone}(max) = \frac{\sqrt{(high^2-low^2)}}{\sqrt{(high^2+(high+low)^2)}} = \frac{13.86}{24.68} = 0.5616$$

Table 4: Random Position of ICA and OCA with Next Position Along with Pheromone

ICA Position	Next Move	P_{mone}	OCA Position	Next Move	P_{mone}
p_3	p_{10}	Exist + 0.0957	p_6	p_{15}	Exist +0.248
p_{15}	p_{12}	Exist +0	p_{14}	p_1	Exist +0
p_{10}	p_1	Exist +0	p_1	p_7	Exist +0.042
p_6	p_4	Exist +0.14	p_{19}	p_{17}	Exist +0
p_8	p_{16}	Exist + 0.0585	p_9	p_{13}	Exist +0.087

The traversal of the ants (ICA and OCA) continues till it reaches the termination criteria explained in previous sections. When any of the ant from both ICA and OCA reaches the $P_{mone}(max)$, the chromosome having greatest P_{mone} from both ICA and OCA is selected. Ranking is used when two or more having same pheromone

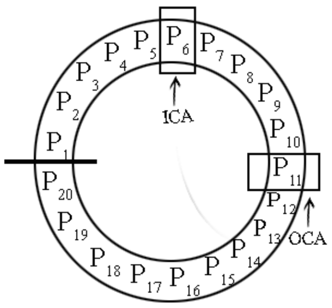

Figure 3: Selection of Parents by Ants having P_{mone} Greater than $P_{mone}(max)$

Ranking of fuzzy path (section 2.5) can be done by the fitness function $f_a(\tilde{A},\tilde{B})$(section 2.4) given in Table 2 and 7.3. Let us consider two individuals p_1(12, 21, 28, 33; 2.54) and p_{17}(32,32,34,39;3.1) are assumed to have same P_{mone} which have to be selected by ranking.

$$R(\tilde{A}) = w(\frac{a+b+c+d}{4})$$

$R(p_1) = 2.54 * \left(\frac{12+21+28+33}{4}\right) = 59.69$ and $R(p_{17}) = 3.1 * \left(\frac{32+32+34+39}{4}\right) = 106.175$

$R(p_1) < R(p_{17})$ and hence p_1 will be selected.

The genetic algorithm performs generations till it attains the termination criteria (section 4.6) and the shortest path 1-3-6-10 is selected as best solution.

8. RESULTS AND DISCUSSIONS

The implementation is carried out in Matlab 8.1 (R_{2013a}) 32 bit student version. The other genetic operations such as chromosome representation, population initialization, crossover and mutation are implemented as explained in the section 4.

The proposed Roulette Ant Wheel Selection (RAWS) method is used for the better selection which concentrate on selecting best individual without affecting the randomness and the term 'natural selection' of the Genetic Algorithm (GA).

The network G={V,E} of up to 50vertices starting from 10 and gradually (10 vertices) increasing the vertices is calculated separately with the edges of generalized trapezoidal fuzzy numbers is established. The algorithm is implemented as per the given description and demonstrated numerical calculation.

The random function with time constraint is used to implement the random moves of both ICA and OCA with unique behaviour. The clockwise traversal is generally achieved for ICA and anticlockwise traversal for OCA is achieved by performing (N-n) clockwise direction moves where N represents population size and n represents the moves that have to be carried out in anti-clockwise directions. The idealness of the best solution of about 5 consecutive generations is taken as termination criteria.

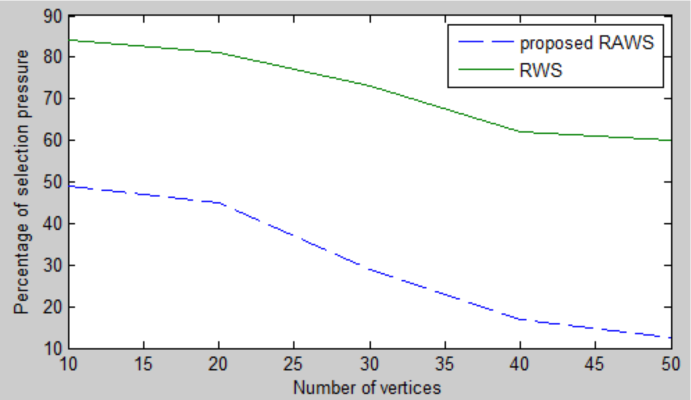

Figure 4: Comparison between Proposed RAWS and RWS on Percentage of Selection Pressure in Various Numbers of Vertices

The selection pressure is defined as the total number of generations taken by the best solution to dominate in the given population and denoted by Sp. The percentage of selection pressure as per [9] is given by

$$Percentage\ Sp = \frac{Sp_{min}}{Sp} \times 100$$

where Sp_{min} represents the minimal possible Sp from all the selection obtained throughout the Genetic Algorithm (GA).

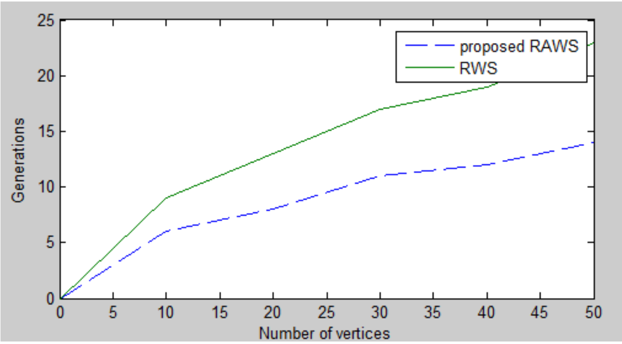

Figure 5: Comparison between Proposed RAWS and RWS on Various Numbers of Vertices

The genetic operations for proposed RAWS and RWS are commonly implemented and the result of number of generations in which the solution obtained is compared along with the various numbers of vertices for both algorithms is shown in Figure 5. This clarifies the advantage and the importance of selection operation in genetic algorithm.

9. CONCLUSIONS AND FUTURE ENHANCEMENT

Fuzzy shortest path problem is solved using the Genetic Algorithm (GA) with the proposed Roulette Ant Wheel Selection (RAWS) which hybrids the characteristics of ants and the roulette wheel selection algorithm. Our objective about analysing importance and the contribution of selection operation in upgrading GA is achieved. The proposed method provides the selection of best solution through certain conditions and also without affecting the originality of the GA 'natural selection'. According to the proposed algorithm, individual of best outcome can be selected with less number of traversal than the better solution which needs comparatively more number of traversal by ants. Thus the survival of worst solution in next generations cannot be possible. The results obtained along various numbers of vertices conclude that the selection operation is more important and its contribution in upgrading the GA is very high and also increases the selection pressure.

The future enhancement of the research is to analyse the other genetic operations such as crossover and mutation where, we already worked on the population initialization. Our futuristic objective is to propose a state of art Genetic Algorithm (GA) by concerning each and every individual operation separately and also in combined manner.

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